CMU SCS

15-826: Multimedia Databases and Data Mining

Data Mining - clustering (revisited)

C. Faloutsos

CMU SCS

Outline

Goal: 'Find similar / interesting things'

- Intro to DB
- Indexing - similarity search
- Data Mining

CMU SCS

Data Mining - Detailed outline

- Statistics
- AI - decision trees
- DB
  - data warehouses; data cubes; OLAP
  - classifiers
  - association rules
  - misc. topics:
    - clustering (revisited)
    - reconstruction of info

CMU SCS

Clustering - outline

- Partitioning methods (eg., k-means)
- Hierarchical methods (eg., agglomerative)
- Density-based methods
- Grid-based methods

CMU SCS

Partitioning methods

K-means (k is given). Goal:

- find k-points and assign the nearest data points to them
- to minimize the sum of squared distances

Algorithm: Iterative improvement

Can be expensive (needs many iterations)

Sensitive to outliers

CMU SCS

Partitioning methods

Variations:

- k-medoids / CLARANS (but: O(n**2))
- k harmonic means [Zhang, Hsu, Dayal+ HPLabs, 99]

CMU SCS

Clustering - outline

- Partitioning methods (eg., k-means)
- Hierarchical methods (eg., agglomerative)
- Density-based methods
- Grid-based methods

CMU SCS

Hierarchical methods

- Agglomerative / Divisive Hierarchical Clustering
- BIRCH
- CURE
- CHAMELEON

CMU SCS

Hierarchical methods

BIRCH:

- uses the 'CF'-tree (count, center, sum of squares, for the points in each node
- needs 1 or 2 passes
- finds spherical clusters
- needs two numbers: branching factor; radius threshold

CMU SCS

Hierarchical methods

BIRCH Algorithm - phase 1:

- start inserting points in the CF-tree (~ a sphere tree)
- if the radius, is exceeded, split the node

phase 2:

- cluster the leaf nodes of the tree

CMU SCS

CURE

Main ideas:

- use sampling
- represent a cluster by many centroids (thus clusters can have arbitrary shapes)

CMU SCS

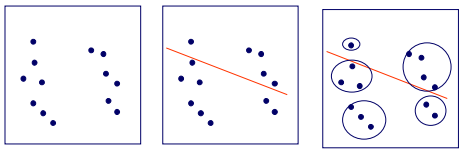
CURE

Algorithm:

- get a sample
- partition it into a set of partitions
- partially cluster each partition
- cluster the partial clusters

CMU SCS

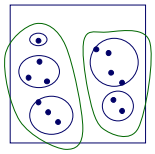
CURE



sample partition partially cluster

CMU SCS

CURE



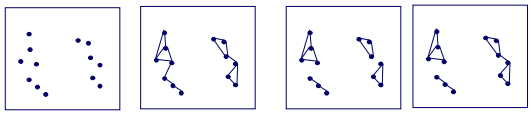
group clusters

- O(n) complexity
- good quality clusters
- relatively small sensitivity to user parameters

CMU SCS

CHAMELEON

- for each object, link it to its k-nn
- use graph partitioning, to create many small clusters (= connected components)
- merge clusters that are 'close enough'



CMU SCS

CHAMELEON

- similarity of a pair of clusters Ci, Cj: use
  - 'relative inter-connectivity' (= avg # of cross-links, normalized)
  - 'relative closeness' (= avg pairwise distance, normalized)
- Empirically: better quality clusters, but $O(n^2)$

CMU SCS

Clustering - outline

- Partitioning methods (eg., k-means)
- Hierarchical methods (eg., agglomerative)
- Density-based methods
- Grid-based methods

CMU SCS

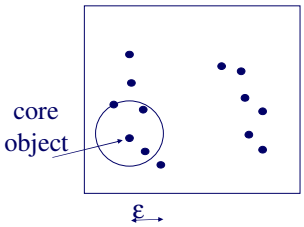
DBSCAN

- High level idea: group high-density areas, that are within a threshold
- in detail: decide on
  - ε: a distance threshold and
  - minPts: minimum number of points in a neighborhood
- 'core object': iff it has >= minPts within ε

CMU SCS

DBSCAN

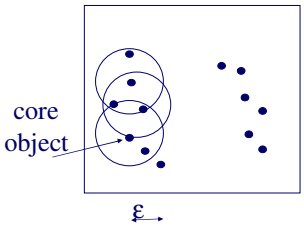
- Pictorially (say, minPts=3):



CMU SCS

DBSCAN

- Pictorially (say, minPts=3):



- 'directly density reachable'
- 'density-connected'

CMU SCS

DBSCAN

- can give elongated clusters
- needs O(n*n) time at worst; less, with a spatial index (but: dim. curse...)
- Also, sensitive to ε (which is global = not adaptive)
- hence: OPTICS

CMU SCS

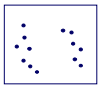
OPTICS

- Given 'minPts'
- impose a sequential ordering on the points
- estimate the 'reachability distance' and
- look for plateaus

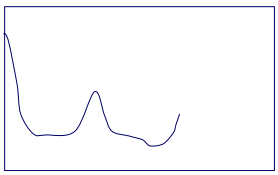
(Details are tricky - intuitively, somehow similar to traversing an MST, and plotting the edge length for each node)

CMU SCS

OPTICS



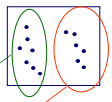
reachability distance



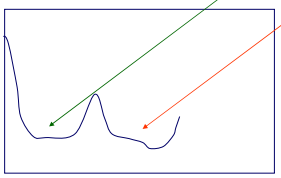
rank of object

CMU SCS

OPTICS



reachability distance



rank of object

CMU SCS

OPTICS

- speed: like DBSCAN (O(n*n), or less, with a spatial index)

CMU SCS

Clustering - outline

- Partitioning methods (eg., k-means)
- Hierarchical methods (eg., agglomerative)
- Density-based methods
- Grid-based methods

CMU SCS

Grid-based methods

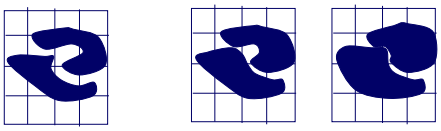
- Main idea: impose a grid; group together 'similar' nearby cells
- STING: do a quad-tree decomposition. For each cell:
  - keep statistics,
  - test (chi-square) whether the distribution is known (uniform, Gauss, etc)
  - merge similar cells together and
  - repeat recursively

CMU SCS

Grid-based methods

'WaveCluster' (2- or 3-d address space)

- do wavelet transform first
- create a hierarchy of clusters, one for each resolution, by grouping the connected components



hi-res med-res low-res

CMU SCS

Grid-based methods

'WaveCluster' : Fast (O(n)), but only for low-dimensionality

CMU SCS

Grid-based methods

'CLIQUE': for high dimensions

'Dense' cell : has >= k points

Goal: find 'dense' cells, in m, or lower, dimensions

CMU SCS

Grid-based methods

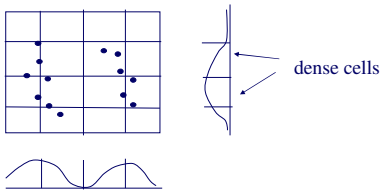
Idea:
- project in lower dimensionalities;
- report dense cells, that are connected
- look for higher-dimensionality dense cells

Uses an 'a-priori'-like argument:
if a cell is 'dense', so are all its projections

CMU SCS

Grid-based methods

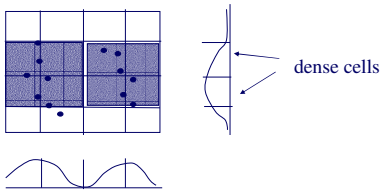
Pictorially:



CMU SCS

Grid-based methods

Pictorially:



CMU SCS

Clustering - outline

- Partitioning methods (eg., k-means)
- Hierarchical methods (eg., agglomerative)
- Density-based methods
- Grid-based methods
- Conclusions

CMU SCS

Conclusions

- O(n) methods: BIRCH, CURE, CLIQUE
- in between: DBSCAN, OPTICS
- O(n*n): CHAMELEON

CMU SCS

Reference

- Han + Kamber, chapter 8.4-8.7